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Aspect sentiment quadruple extraction based on the sentence-guided grid tagging scheme

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Abstract
The aspect sentiment quadruple extraction (ASQE) task aims to extract all the opinion quadruples (aspect term, aspect category, opinion term, sentiment polarity) from the review text. However, there are often implicit expressions in the review text, and implicit opinion quadruples are difficult to be represented and extracted. To this end, we propose a novel end-to-end approach for the explicit and implicit ASQE tasks. Specifically, we use a multi-scale convolutional neural network (MS-CNN) and bidirectional long short-term memory neural network (BiLSTM) to capture the local features and contextual features. Then we design a novel sentence-guided grid tagging scheme to extract explicit and implicit opinion quadruples contained in the reviews, in which the grid of the representation of the sentence's overall meaning is used to mark the implicit expression. Extensive experimental results indicate that our model outperforms strong baselines significantly and achieves state-of-the-art performance.

Keywords Aspect sentiment quadruple extraction · Aspect-based sentiment analysis · Natural language processing · Information extraction

1 Introduction

With the rapid development of the Internet, massive users express their opinions on products and events on online platforms, which establish an important corpus foundation for aspect-level sentiment analysis [1]. Aspect-based sentiment analysis (ABSA) identifies people's attitudes toward the opinion targets, which can be widely applied in many realistic scenarios [2]. For example, the result of ABSA of product reviews under e-commerce platforms can show users' desire to purchase and help enterprises improve the quality of products [3, 4], and the result of ABSA of event comments under social platforms can help organizations

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discover current and future hot spots and take measures to guide [5]. Therefore, ABSA has gradually become the focus of research [6–8].

The ABSA task consisted of many subtasks. Aspect term extraction (ATE) aims to extract all aspect terms from the review texts, while opinion term extraction (OTE) aims to extract all opinion terms. With the demand for deeper mining of review text, people began to pay more attention to the study on the joint prediction of multiple sentiment elements than the studies that only extract a single sentiment element. Pair extraction aims to jointly extract two sentiment elements, such as Aspect-Opinion Pair Extraction (AOPE) [9–12], and Aspect Category Sentiment Analysis (ACSA) [13–15]. In addition, the study works on triplet extraction have also made significant progress, such as Aspect Sentiment Triplet Extraction (ASTE) [16–21] and Aspect-Category-Sentiment Detection (ACSD) [22–25]. Since there are too many aspect terms in the corpus, even the same aspect can be described by many different aspect terms. Therefore, aspect sentiment quadruple extraction task was proposed [26, 27]. Aspect sentiment quadruple extraction (ASQE) is a finer-grained ABSA task, which aims to extract all opinion quadruples (aspect term, aspect category, opinion term, sentiment polarity) from reviews [26]. Specifically, the aspect term is the target of an opinion, the aspect category is the predefined category of the aspect term, the opinion term is a word or phrase that describes the aspect term, and the sentiment polarity is the sentiment (e.g. positive, negative, neutral) expressed by the opinion term. There are too many subtasks of ABSA, so some people try to construct a unified ABSA model which can narrow the gaps between the modeling divergences of subtasks of ABSA and can be used to process multiple different ABSA subtasks at the same time [12, 28, 29]. The example of these subtasks is shown in Figure 1.

ASQE is a recently proposed task, and there are few research works related to it. Some models [26] use a sequence tagging scheme to label opinion elements for the ASQE task. However, when there are one-to-many or many-to-one relationships between aspect terms and opinion terms in a review, the sequence tagging will be complicated. PARAPHRASE [27] uses the paraphrase generation method to deal with ASQE tasks, but it does not take the implicit opinion term into consideration. Review texts often contain implicit expressions, including implicit aspect terms and opinion terms. For example, in the review text "*today, it stopped powering on*", although we can infer that the person meant that the computer's operation performance is poor, neither the aspect term *operation performance* nor the opinion

Sentence: Coffee is a better deal than overpriced Cosi sandwiches	
Aspect Term Extraction（ATE） • Coffee • Cosi sandwiches	Opinion Term Extraction（OTE） • better • overpriced
Aspect-Opinion Pair Extraction （AOPE） • （Coffee，better） • （Cosi sandwiches，overpriced）	Aspect Category Sentiment Analysis（ACSA） • （FOOD，positive） • （FOOD，negative）
Aspect Sentiment Triplet Extraction （ASTE） • （Coffee，better，positive） • （Cosi sandwiches，overpriced，negative）	Aspect-Category-Sentiment Detection（ACSD） • （Coffee，FOOD，positive） • （Cosi sandwiches，FOOD，negative）
Aspect Sentiment Quadruple Extraction（ASQE） • （Coffee，FOOD，better，positive） • （Cosi sandwiches，FOOD，overpriced，negative）	

Figure 1 The example of some subtasks of ABSA. The word or phrase in red is the aspect term, yellow is the aspect category, blue is the opinion term, and green is the sentiment polarity

term *poor* explicitly exist in the review text, so this is a review text containing an implicit aspect term and an implicit opinion term. Therefore, we propose an end-to-end framework for the explicit and implicit ASQE tasks (**SGTS-AQSE**), which can extract the four opinion elements at the same time. Firstly, we use multi-scale convolutional neural network (MS-CNN) [30] and bidirectional long short-term memory network (BiLSTM) [31] to capture important information in the sentence. Then, we extract the overall meaning of the sentence using self-attention mechanism [32] and max pooling [33], which is used to process implicit aspect terms and opinion terms. Finally, base on GTS [34], we design a novel **S**entence-**g**uided **G**rid **T**agging **S**cheme (**SG-GTS**) to encode and decode the implicit and explicit aspect terms and opinion terms in the sentence. The SG-GTS uses two grids to extract opinion triples and aspect categories, and the relationship between the sentiment factors can be inferred from the position of their labels in the grid. This is the first time the grid tagging scheme has been applied to the ASQE task. Furthermore, we set the special label for the implicit aspect term and opinion term.

The main contributions of our work can be summarized as follows:

- We design a novel scheme SG-GTS to label and extract the quadruples, in which the word-pair relations in the review text form grids. The quadruple extraction task is cleverly transformed into the grid generation task. We especially take the implicit expressions in sentences into account in the scheme.
- We propose an end-to-end framework for the ASQE task. The model is able to extract aspect term, opinion term, sentiment polarity, and aspect category at the same time, rather than in a pipeline method. Hence, it can avoid the error propagation problem, and make full use of the interactive relations between the substacks.
- We design a special scheme to capture sentence features by adopting MS-CNN and BiLSTM, which can better combine local and contextual features to capture enriched high-dimensional feature representation.
- Experimental results on two public datasets show that our model outperforms the state-of-the-art (SOTA) methods. Especially, our model outperforms the SOTA model by 4.15% on the Restaurant-ACOS dataset.

2 Related work

2.1 Aspect sentiment quadruple extraction

Traditional sentiment analysis mainly analyzes sentiment polarity at the document or sentence level [35–37]. ABSA is a finer-grained sentiment analysis task, used to analyze the user's opinion of the aspect of the product or service, and can be divided into many subtasks according to the extracted opinion elements. The ASTE task aims to extract (aspect term, opinion term, sentiment polarity) [16–21]. However, there are too many aspect terms in the review texts in the real scene. Therefore the distribution of the extracted aspect sentiment triplets of the ASTE task is too wide. Therefore, the ACSD task has gradually become a research focus [22–25]. It extracts the triples (aspect term, aspect category, sentiment polarity) from the review text.

With the increasing demand for sentiment analysis, the ASQE task is proposed. Compared with the ASTE and ASCD tasks, it extracts all four opinion elements and constructs the opinion quadruple (aspect term, aspect category, opinion term, sentiment polarity). Cai et al. [26] proposes four baseline methods for the ASQE task and considers how to extract quadruplets when the sentences contain implicit aspect terms or opinion terms. Zhang et al. [27] proposes a paraphrase modeling paradigm to predict the quadruplets. Li et al. [38] proposes to extract the sentiment quadruple in a dialogue. However, the model extracts the sentiment quadruple of target-aspect-opinion-sentiment instead of aspect-category-opinion-sentiment. There are two main challenges in the ASQE task. One is how to use the interactive relationships between the four opinion elements fully. The other is how to extract the implicit expressions in the review text, including implicit aspect terms and opinion terms.

2.2 Implicit expression

In the sentiment analysis task, $explicit$ means the word or phrase exists directly in the review text, while $implicit$ is the opposite. For example, in the review sentence "*i had to ask her three times before she finally came back with the dish ive requested*", there is one quadruple that needs to be extracted: Null-Service-Null-Negative. It is very common for a review text to contain implicit expressions, and there have been some works on the implicit aspect detection task and implicit opinion detection task. Areed et al. [39] proposed a rule-based ABSA model to detect explicit and implicit aspects and identify their corresponding sentiment polarities. The model looks for implicit aspect terms based on the lexicon. Eldin et al. [40] used a set of linguistic and heuristics patterns to extract implicit aspect terms. Lazhar et al. [41] exploited relations between concepts, individuals, and attributes to extract implicit feature-opinion pairs. However, only a little work tries to extract implicit aspect terms and implicit opinion terms with a unified framework.

2.3 End-to-end aspect-based sentiment analysis

Many previous studies used pipeline method to process ABSA tasks. However, the pipeline method has an error propagation problem and cannot fully exploit the interaction between the substacks [13]. Different from the pipeline method, the end-to-end method simultaneously extracts aspect terms and their corresponding sentiment polarities from the review text, which can make full use of the interactive relations between the subtasks [17, 42, 43]. Tagging scheme is one of the ways to construct an end-to-end framework. Peng et al. [16] proposed a joint approach JET to extract the opinion triplets simultaneously based on a position-aware tagging scheme. The sequence tagging scheme will be complicated if there is more than one aspect term or one opinion term in the review text. Therefore, [34] proposed a unified grid tagging scheme (GTS) to address the ASPE and ASTE, which can extract the relationship between all word pairs in the sentence. However, GTS cannot mark implicit aspect terms and opinion terms in the grid, and cannot be used to extract the opinion quads.

3 Methodology

3.1 Task definition

The goal of our model is to extract all opinion quadruples from the given review. Specifically, given a review text $X = \{x_1, x_2, \ldots, x_n\}$ with n words and a set of predefined aspect categories $C = \{c_1, c_2, \ldots, c_m\}$ with m aspect categories, the goal of the ASQE task is to extract all quadruples $T = \left\{(a, c, o, s)_t\right\}_{t=1}^{|v|}$ from the review text, where $(a, c, o, s)_t$ is the

t-th quadruple in the review. The symbols a, c, o, s represent aspect term, aspect category, opinion term, and sentiment polarity, respectively, and $c \in C$. v is the number of opinion quadruplets in X.

3.2 Model architecture

The SGTS-ASQE model architecture is shown in Figure 2.

The model first preprocesses the review text, which utilizes a pre-trained embedding model to convert each word into a word embedding representation and takes them as the input of the proposed model. Then comes the feature extraction step. The model uses MS-CNN [30] to extract local features. In addition, the review text is context-dependent, so the model uses BiLSTM [31] to capture the long-term dependencies within the sentence. Through them, we construct the enriched high-dimensional feature representation of the review text. In the review text, aspect terms and opinion terms sometimes exist in the form of implicit expressions. The model uses the self-attention mechanism [32] and max pooling [33] to construct the sentence's overall meaning to extract these implicit expressions. We concatenate the sentence feature representation and the overall sentence feature representation used as the

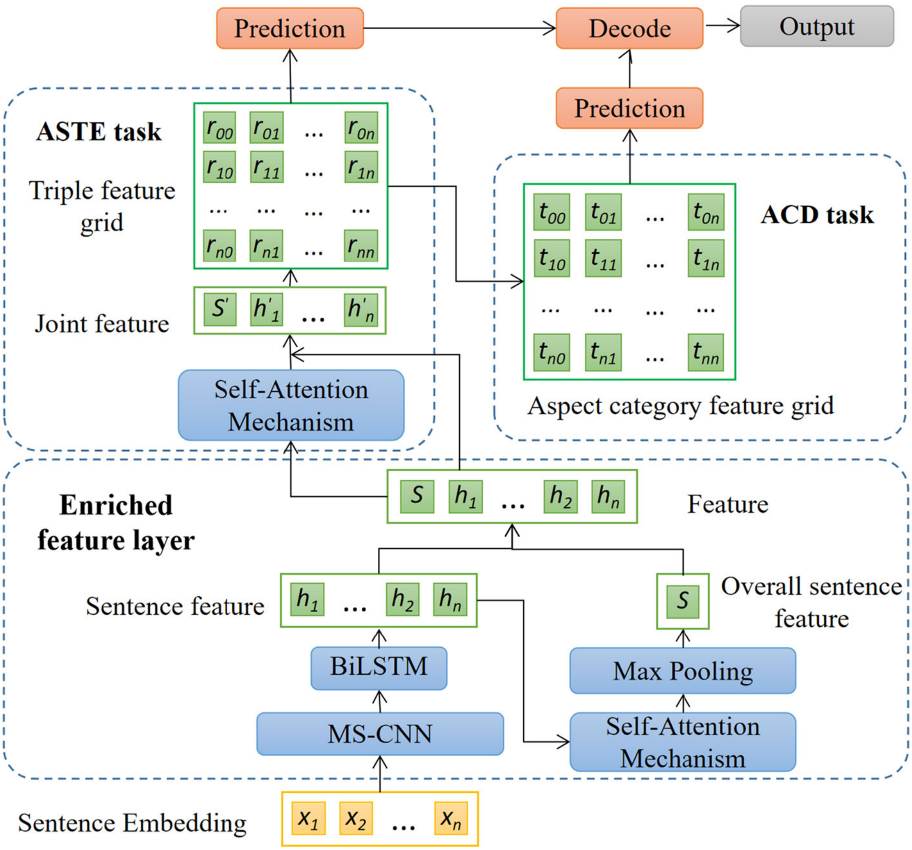

Figure 2 The architecture of SGTS-ASQE

feature representation of the sentence, which contains both explicit and implicit emotional elements. To accurately extract all quadruples in the sentence, we design a grid tagging scheme for both explicit and implicit expression and its decoding method. The quadruple extraction task is transformed into a grid prediction task. Each word-pair relationship is mapped into the grid so that the relationship between sentiment elements is fully considered. The model uses the feature representation of the sentence to construct the triple feature grid, which is also used to generate the aspect category feature grid. Finally, the model decodes the ASTE and ACD tasks' prediction results to obtain the opinion quadruplets.

Next, we will detail the individual modules of the model.

3.3 Sentence-guided grid tagging scheme

Earlier studies usually use the sequence tagging scheme to process the ABSA task [16, 44, 45]. But the one-to-many and many-to-one relationships between aspect terms and opinion terms may lead to a complex sequence labeling scheme. Wu et al. [34] proposed the grid tagging scheme to capture word-to-word interactions in sentences. However, these tagging schemes often ignore implicit aspects and opinions in the sentence. Therefore, based on the grid tagging scheme, we propose the SG-GTS to capture both explicit and implicit expressions in sentences. The SG-GTS uses eight labels $\{N, A, O, Mixed, Pos, Neg, Neu, C\}$ to label the relationship between all word pairs in the sentence. N represents that the words in the word pair are not related. A and O respectively represent that the words in the word pair belong to the same aspect term and opinion term. $Mixed$ represents that the words in the word pair belong to both the aspect term and opinion term. Pos, Neg, and Neu represent the sentiment polarity of the word pair. C represents that the word pair belongs to one of the predefined aspect categories. In addition, there are several overlap rules between these tags. $Mixed$ can cover A and O. Pos, Neg, Neu, and C can cover A, O, and $Mixed$. Figures 3 and 4 show the examples of the SG-GTS, and S in the figures represents the meaning of the overall sentence. The grids marked in red and blue represent the word pairs belonging to the same aspect term and opinion term, respectively. The grid marked in purple represents that the word pair has sentiment polarity and aspect category.

Figure 3 is the first example of the SG-GTS. The sentence has an explicit aspect term and an implicit opinion term. The label of the word pair $(backlight, backlight)$ is A, so $backlight$ is an aspect term in the sentence. Since S represents the meaning of the overall sentence and the sentence contains an implicit opinion term, the label of the word pair (S, S) is O. The labels of the word pair $(backlight, S)$ are Neg and c_2, which means that the word pair $(backlight, S)$ contains negative sentimental polarity and the aspect term $backlight$ belongs

S	yesterday	the	backlight	went	out	
O	N	N	Neg, c_2	N	N	S
	N	N	N	N	N	yesterday
		N	N	N	N	the
			A	N	N	backlight
				N	N	went
					N	out

Figure 3 The first example of the SG-GTS. A quadruple in the sentence is $\{backlight, c_2, -1, negative\}$

S	regret	buying	it	at	times	
Neg, c_1	N	N	N	N	N	S
	N	N	N	N	N	regret
		N	N	N	N	buying
			N	N	N	it
				N	N	at
					N	times

Figure 4 The second example of the SG-GTS. A quadruple in the sentence is $\{-1, c_1, -1, negative\}$

to c_2, $c_2 \in C$. In particular, c_2 is actually in another grid, which is called aspect category grid, here we draw aspect category and opinion triple in the same table for convenience.

Figure 4 is the second example of the SG-GTS. The sentence has the implicit aspect and opinion, so the label of word pair (S, S) is $Mixed$. Since the word pair (S, S) is located on the main diagonal of the grid, according to the label covering rule, the label Neg covers the label A and O. The labels of the word pair (S, S) are Neg and c_1, which means that the implicit word pair contains negative sentiment polarity and the implicit aspect term belongs to c_1, $c_1 \in C$.

These examples show that the SG-GTS can successfully transform the task of ASQE into a unified labeling task by labeling the relationships between all word pairs, and the scheme takes implicit expressions in sentences into account.

3.4 Enriched feature layer

Given a review text $X = \{x_1, x_2, \ldots, x_n\}$, the model first uses MS-CNN and BiLSTM to capture the enriched word feature representation H in the sentence. Considering that there may be implicit expressions in the sentence, the model further constructs the overall representation of the sentence S:

$$H_s = Attention\left(HW_s^Q, HW_s^K, HW_s^V\right) \tag{1}$$

$$S = MaxPooling\,(H_s) * W_s \tag{2}$$

where $Attention$ is the method for calculating the attention representation, $MaxPooling$ is the max-pooling layer used to obtain the maximum value of the same dimension, W_s^Q, W_s^K, W_s^v, and W_s are the weight parameters to be trained.

To better construct the feature representation of the sentence, the model splices the above feature representations and redefines the enriched feature representation H:

$$H = [S : H] \tag{3}$$

where [:] is the operation to concatenate the vectors.

3.5 Tasks of ASTE and ACD

Based on the enriched feature representation H, the model uses the self-attention mechanism to mine important information, thereby obtaining the more enriched feature representation $H^{'}$:

$$H^{'} = Attention\left(HW^{Q}, HW^{K}, HW^{V}\right) \tag{4}$$

where $Attention$ is the method of calculating the attention representation, W^{Q}, W^{K}, and W^{v} are the weight parameters to be trained.

Then the model splices the feature representations of words i and j and uses this as triple feature representation R for ASTE task. Based on the triple feature representation R, the model can further capture the aspect category feature representation T:

$$r_{ij} = \left[H_{i}^{'} : H_{j}^{'}\right] \tag{5}$$

$$t_{ij} = W_{t} r_{ij} \tag{6}$$

where [:] is the operation to splice the vectors, W_t is the weight parameter to be trained.

Next, the model predicts the corresponding relationship for each word pair through the fully connected layer:

$$\hat{Y}_{ij}^{aste} = softmax\left(W^{aste} r_{ij} + b^{aste}\right) \tag{7}$$

$$\hat{Y}_{ij}^{acd} = softmax\left(W^{acd} t_{ij} + b^{acd}\right) \tag{8}$$

where W^{ast}, b^{ast}, W^{acd} and b^{acd} are the weight parameters to be trained. $\hat{Y}_{ij}^{aste}$ is the prediction of the triple grid, and $\hat{Y}_{ij}^{acd}$ is the prediction of the aspect category grid.

3.6 Decoding algorithm for SG-GTS

The SGTS-ASQE model obtains the prediction matrices (R and T) of the ASTE task and ACD task based on Section 3.5, $R, T \in \mathbb{R}^{(n+1)\times(n+1)}$. The process of the decoding algorithm for SG-GTS is shown in Algorithm 1.

The sentiment polarity s and the aspect category c in the aspect sentiment quadruple are determined according to the majority voting mechanism [46].

3.7 Loss function

The training target of the SGTS-ASQE model is to minimize the loss L, which consists of the loss L_{aste} of the ASTE task and the loss L_{acd} of the ACD task. We use the cross entropy loss to calculate the loss between the true label distribution and the predicted label distribution (y^{aste} and $\hat{y}^{aste}$, y^{acd} and $\hat{y}^{acd}$):

$$L = \alpha_1 L_{aste} + (1 - \alpha_1) L_{acd} \tag{9}$$

$$Z_1 = \sum_{i=1}^{n} \sum_{j=i}^{n} \sum_{k \in D} f\left(y_{ij}^{aste} = k\right) log\left(\hat{y}_{ij|k}^{aste}\right) \tag{10}$$

Algorithm 1 Decoding algorithm for SG-GTS

Input: The prediction matrices R and T, $R, T \in \mathbb{R}^{(n+1)\times(n+1)}$, where n represents the predicted label of the word pair.
Output: The set of aspect opinion quadruples, Q. Each quadruple can be represents as (a, c, o, s) , where a represents aspect term, c represents aspect category, o represents opinion term, and s represents the sentiment polarity.

The set of aspect opinion quadruple $Q \leftarrow []$
The set of aspect term $Aspect \leftarrow []$
The set of opinion term $Opinion \leftarrow []$
while the indices $0 \leq l, r \leq n+1$ **do**
  if $R_{00} = A \vee R_{00} = Mixed$ **then**
    $Aspect \leftarrow Aspect \cup \{-1\}$
  end if
  if $R_{00} = O \vee R_{00} = Mixed$ **then**
    $opinion \leftarrow Opinion \cup \{-1\}$
  end if
  while $l \leq i \leq r$ **do**
    if all $R_{ii} = A \vee$ all $R_{ii} = Mixed$ **then**
      take the words $\{w_l, \ldots, w_r\}$ as a aspect term a
      $Aspect \leftarrow Aspect \cup \{a\}$
    end if
    if all $R_{ii} = O \vee$ all $R_{ii} = Mixed$ **then**
      take the words $\{w_l, \ldots, w_r\}$ as a opinion term o
      $Opinion \leftarrow Opinion \cup \{o\}$
    end if
  end while
end while
while the aspect term $a \in Aspect$ & the opinion term $o \in Opinion$ **do**
  while $w_i \in a$ & $w_j \in o$ **do**
    if R_{ij} has the sentiment polarity s and T_{ij} has the aspect category c **then**
      $Q \leftarrow Q \cup (a, c, o, s)$
    end if
  end while
end while

$$L_{aste} = Z_1 + \lambda_{aste} \parallel w_{aste} \parallel_2^2 \tag{11}$$

$$Z_2 = \sum_{i=1}^{n} \sum_{j=i}^{n} \sum_{k \in C} f\left(y_{ij}^{acd} = k\right) log\left(\hat{y}_{ij|k}^{acd}\right) \tag{12}$$

$$L_{acd} = Z_2 + \lambda_{acd} \parallel w_{acd} \parallel_2^2 \tag{13}$$

where f () is a function which can determine whether the equation in parentheses is correct. i and j represent the indices of the word pair (w_i, w_j). D represents the label of the sentiment polarity of the ASTE task, $D = \{N, A, O, Pos, Neg, Neu\}$. C is the predefined aspect category label set. λ_{aste} and λ_{acd} is the penalty parameter in $L2$ regularization to avoid the overfitting problem of the model. α_1 is the parameter.

Table 1 The statistics of ACOS dataset

Opinion Element & Tuple	Symbol	Restaurant-ACOS	Laptop-ACOS
Review Text	X	2286	4076
Aspect Term	a	3110	4958
Aspect Category	c	2967	4992
Opinion Term	o	3335	5378
Sentiment Polarity	s	3110	4958
Aspect-Sentiment	(a, s)	3155	5035
Aspect-Opinion	(a, o)	3571	5726
Aspect-Opinion-Sentiment	(a, o, s)	3575	5731
Aspect-Category-Sentiment	(a, c, s)	3335	5227
Aspect-Category-Opinion-Sentiment	(a, c, o, s)	3658	5758

4 Experiments

4.1 Datasets and settings

Datasets We evaluate the SGTS-ASQE model on Restaurant-ACOS and Laptop-ACOS [26]. The datasets consist of the reviews of the restaurant and laptop, respectively. The statistics for these datasets are listed in Table 1. To evaluate the performance of the proposed model, each dataset was divided into the training dataset, validation dataset, and test dataset, which is shown in Table 2. We use P, R and $F1$ as evaluation indicators for the ASQE task.

Settings Compared with pre-trained models such as BERT, using Glove [47] to generate word embeddings can greatly save memory and running time. So, We use Glove to initialize the word vectors and the dimension of word vectors is 300. The batch size is set as 32 examples, and the maximum length of the review is set as 128. To avoid model from being overfit, dropout is set as 0.32, and the penalty parameters λ_{aste} and λ_{acd}in formula (11) and (13) are set as 2e-5. We initialize the other parameters in the model from a uniform distribution $U\ (-\epsilon, \epsilon)$, Adam [48] is used as the optimizer for the parameters, and the learning rate is set as 1e-3. We run our model three times with different seeds and report the average result of them.

4.2 Baselines

To demonstrate the effectiveness of SGTS-ASQE for the ASQE task, we compare it with the following baselines proposed in [26].

Table 2 The division of ACOS dataset

Dataset	Restaurant-ACOS	Laptop-ACOS
Train	1531	2934
Dev	170	326
Test	585	816

- **Double-Propagation-ACOS**: The Double-Propagation-ACOS model is a rule-based model for the ASQE task, which is based on the Double Propagation (DP) algorithm [49]. First, the model follows the DP algorithm to extract the triples (a, o, s), where the model utilizes the syntactic relations and the sentiment lexicon. Then, the model identifies the aspect category of each extracted triple.
- **JET-ACOS**: Firstly, the model obtains the candidate triples (a, o, s) in each review based on JET [45], where the JET uses a position-aware scheme to jointly extract the aspects, opinion, and sentiment polarity. Then, design a BERT-based model to get the aspect category of the extracted triples.
- **TAS-BERT-ACOS**: TAS-BERT is a multi-task learning framework for the ACSA task [50]. TAS-BERT-ACOS adopts the input transformation strategy in TAS-BERT to perform category-sentiment conditional aspect-opinion co-extraction to get candidate quadruples, and uses a quadruple filter to obtain the final quadruples.
- **Extract-Classify-ACOS**: It is proposed based on the aspect-opinion co-extraction system [51]. It extracts the explicit aspect-opinion pairs based on a CRF layer with the modified BIO tagging scheme, and uses [CLS] tokens to predict implicit aspects and opinions. The model obtains candidate quadruples by the way of multiple multi-class classifications.

4.3 Comparison results

The comparison results for all methods are shown in Table 3, and the top-performing data is highlighted in bold in the table.

The SGTS-ASQE model achieves state-of-the-art performance. The one reason is the combination of MS-CNN and BiLSTM. The model can better capture the multi-scale local and global features in sentences. In addition, the model designs a novel grid tagging scheme and its decoding method. It can use a multi-task framework to extract the explicit and implicit aspect opinion quadruples in sentences. The model's performance on the ASQE task in different datasets of different domains is different. Compared with the laptop domain, the SGTS-ASQE can get better performance on Restaurant-ACOS. This is mainly because there are too many professional words in the laptop domain..

Firstly, the Double-Propagation-ACOS model based on syntactic relations and sentiment lexicon relies too much on the quality of the constructed rules. However, language has the characteristic that it is complex and variable. Our model can better learn the feature between each word in the sentences through the neural network framework, and it has higher flexibility. Secondly, our model has better performance than The JET-ACOS model, which shows that the SG-GTS can better locate the information of aspect opinion quadruple in sentences and make full use of the independent and joint information between tasks than the position-aware

Table 3 The result of the experiment on the ASQE task

Model	Restaurant-ACOS			Laptop-ACOS		
	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)
Double-Propagation-ACOS	34.67	15.08	21.04	13.04	0.57	8.00
JET-ACOS	59.81	28.94	39.01	44.52	16.25	23.81
TAS-BERT-ACOS	26.29	46.29	33.53	47.15	19.22	27.31
Extract-Classify-ACOS	38.54	52.96	44.61	45.56	29.48	35.80
SGTS-ASQE	55.24	43.69	**48.76**	41.44	32.26	**36.28**

scheme JET. Thirdly, the implicit opinion quadruples in reviews will have a certain impact on the CRF model, so the performance of the TAS-BERT-ACOS model is slightly poor. Fourth, it can be seen that our model has better performance on F1 than the Extract-Classify-ACOS, which shows that compared with the pipeline method, the end-to-end method can better capture the interaction information between the aspect opinion quadruple subtasks. In addition, the performance of the prediction on the ATE task and the OTE task is positively correlated with the performance of the prediction on the ASQE task. Therefore, we compare the performance of the SGTS-ASQE model in four different kinds of ASQE tasks. The results are shown in Table 4. By analyzing Table 4, it can be found that the SGTS-ASQE model has great advantages in extracting $(explicit\ a, c, explicit\ o, s)$ and $(implicit\ a, c, explicit\ o, s)$. The main reasons are as follows. Firstly, the SG-GTS is a variant of the method of explicit ASTE tasks, so it has natural advantages for dealing with explicit aspect terms and opinion terms. Secondly, it is more difficult to extract implicit opinion terms accurately than implicit aspect terms. The implicit aspect term is mainly expressed by nickname and ellipsis. The opinion term can be expressed by metaphor, satire, and other ways, while the expression of implicit opinion term is more complicated and hard to be captured by grid. Third, the SG-GTS can extract at most one $(implicit\ a, c, implicit\ o, s)$ from a review text. Hence, the model performs excellently at extracting $(implicit\ a, c, explicit\ o, s)$ but is poor at extracting $(implicit\ a, c, implicit\ o, s)$. All in all, our model has state-of-the-art performance on extracting quadruples that do not contain implicit opinion term.

Furthermore, we study the performance of SG-GTS on other ABSA subtasks on the same dataset. The result of the experiment is shown in Table 5.

We can find that with the increase of opinion elements, the extraction performance decreases by comparing (ATE, AOPE, ASTE) or (OTE, AOPE, ASTE) or (ATE, ACSA, ACSD). It is because the probability of mismatching and missing elements increases as the opinion elements and the dependencies between them increase. We can find that the performance of extracting tuples containing the aspect category is better than that of tuples not containing the aspect category on the Restaurant-ACOS dataset by comparing (AOPE, ACSA)

Table 4 The experiment results of the F1 scores of explicit and implicit ATE and OTE task. "EAEO" refers to the task that extracts the aspect sentiment quadruples like $(explicit\ a, c, explicit\ o, s)$, "EAIO" extracts $(explicit\ a, c, implicit\ o, s)$, "IAEO" extracts $(implicit\ a, c, explicit\ o, s)$, "IAIO" extracts $(implicit\ a, c, implicit\ o, s)$

Dataset	Model	Target Task			
		EAEO	IAEO	EAIO	IAIO
Restaurant-ACOS	Double-Propagation-ACOS	26.02	-	-	-
	JET-ACOS	52.30	-	-	-
	TAS-BERT-ACOS	33.60	31.84	14.03	**39.76**
	Extract-Classify-ACOS	44.96	34.66	**23.86**	33.70
	SGTS-ASQE	**56.02**	**39.59**	11.08	29.61
Laptop-ACOS	Double-Propagation-ACOS	9.80	-	-	-
	JET-ACOS	35.70	-	-	-
	TAS-BERT-ACOS	26.10	41.54	10.90	**21.15**
	Extract-Classify-ACOS	35.39	39.00	16.82	18.58
	SGTS-ASQE	**36.58**	**52.45**	**17.24**	14.62

Table 5 The result of the experiment on other ABSA subtasks

Task	Restaurant-ACOS P(%)	R(%)	F1(%)	Laptop-ACOS P(%)	R(%)	F1(%)
ATE	72.99	62.88	67.56	74.80	60.33	66.79
OTE	68.80	60.78	64.54	77.10	60.25	67.64
AOPE	59.40	50.17	54.40	67.97	50.80	58.15
ACSA	73.62	58.37	65.11	54.70	42.12	47.59
ASTE	60.84	48.82	54.17	65.24	46.60	54.34
ACSD	63.51	49.04	55.35	44.83	34.59	39.05

or (ASTE, ACSD). On the Laptop-ACOS, it is the opposite. It is because the number of aspect categories in the Restaurant-ACOS dataset is much less than that in the Laptop-ACOS. Therefore, the extraction performance of tuples containing aspect categories dramatically correlates with the number of categories.

5 Analysis

5.1 Ablation study

To study the impact of different modules of the model on the performance of the whole model, we respectively removed the CNN module, BiLSTM module, and overall sentence feature S from the SGTS-ASQE for the ablation experiment. The result of the F1 score of ablation experiment is shown in Table 6, the top-performing data is highlighted in bold in the table, "w / o" means "no".

Through observation, it can be found that each module of the SGTS-ASQE model can improve the model's performance. After removing CNN or BiLSTM module, the performance of the SGTS-ASQE model decreases sharply, which shows that the combination of global contextual features and local features can help the model understand the sentence better. In addition, the performance of the SGTS-ASQE model decreases significantly after removing the overall sentence feature S. It confirms that the overall sentence feature can help predict the implicit aspect opinion quadruples in the review text to effectively improve the model's performance.

5.2 Effects of the parameters

The model needs to aggregate the loss functions of subtasks into a total loss function. To study the influence of weight proportion of loss function on our model, we conducted exper-

Table 6 Ablation study

Model	Restaurant-ACOS	Laptop-ACOS
SGTS-ASQE	**48.76**	**36.28**
w/o CNN	38.10	26.80
w/o BiLSTM	40.70	31.80
w/o S	38.43	31.48

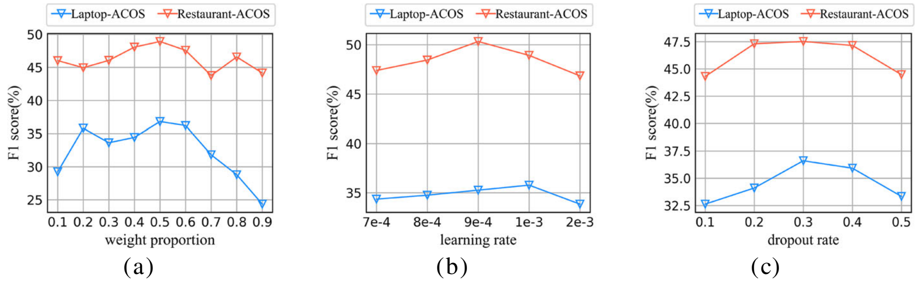

Figure 5 Effects of the parameters

iments on the datasets. We set the learning rate as 1e-3. The experimental results are shown in Figure 5(a). Through observation, it can be noted that both subtasks contribute to the ASQE task, and reasonably setting the weight proportion of the loss function can improve the performance of the SGTS-ASQE model, and the SGTS-ASQE model can obtain the best performance when the weight proportion α_1 is set to 0.5.

In addition to the weight proportion of the loss function, there are other parameters that also have an impact on the model. Therefore, we investigate the effect of different learning rates and dropout rates on the model. The experimental results are shown in Figure 5(b) and (c).

5.3 Case study

To better understand the behavior of SG-GTS, we conduct a case study in this section. We selected 5 representative cases from the Restaurant-ACOS dataset for presentation and explanation, as shown in Figure 6.

Sentence-1: green tea creme brulee is a must ! Gold Label: (green tea creme brulee, FOOD#QUALITY, must, POS) Prediction Label: (green tea creme brulee, FOOD#QUALITY, must, POS) √
Sentence-2: yum! Gold Label: (NULL, FOOD#QUALITY, yum, POS) Prediction Label: (NULL, FOOD#QUALITY, yum, POS) √
Sentence-3: the food is great , the bartenders go that extra mile . Gold Label: (food, FOOD#QUALITY, great, POS), (bartenders, SERVICE#GENERAL, NULL, POS) Prediction Label: (food, FOOD#QUALITY, great, POS) √
Sentence-4: drinks are suberb , and i feel like i am in a third world country when i walk in the door . Gold Label: (drinks, DRINKS#QUALITY, suberb, POS), (NULL, AMBIENCE#GENERAL, NULL, POS) Prediction Label: (drinks, DRINKS#QUALITY, suberb, POS) √
Sentence-5: the lemon chicken tasted like sticky sweet donuts and the honey walnut prawns , the few they actually give you . . . . . were not good . Gold Label: (lemon chicken, FOOD#QUALITY, sticky sweet donuts, NEG), (honey walnut prawns, FOOD#QUALITY, not good, NEG), (honey walnut prawns, FOOD#STYLE_OPTIONS, not good, NEG) Prediction Label: (lemon chicken, FOOD#QUALITY, sticky sweet donuts, NEG) √, (honey walnut prawns, FOOD#QUALITY, not good, NEG) √

Figure 6 Cases containing the input sentence, gold label and predicted quads

In Sentence-1, the aspect and opinion terms exist explicitly, and the model accurately predicted the quadruple. There is an implicit aspect in Sentence-2. To extract a quadruple containing implicit expressions, we need to understand the meaning of the overall sentence. We can infer that this review text evaluates a certain dish. Sentence-3 contains two opinion quadruples, of which only the quadruple containing explicit aspect and opinion is successfully extracted. As our experiments have proved, the implicit opinion is difficult to be accurately extracted due to its complex form, which is also confirmed in sentence-4. There is an explicit opinion quadruple in Sentence-5 that was not extracted. After analysis, there are two quadruples that have the same aspect term and opinion term. The aspect term is *honey walnut prawns*, and the opinion term is *not good*. In SG-GTS, each word pair in the grid can only have one aspect category label and one sentiment polarity label, so *FOOD#STYLE_OPTIONS* is covered by *FOOD#QUALITY* in the aspect category feature grid.

6 Conclusion

We propose an end-to-end framework for the ASQE task, which jointly learns the ASTE task and the ACD task. The SGTS-ASQE model uses MS-CNN and BiLSTM to capture enriched high-dimensional feature representation in the sentences. Furthermore, we designed a novel sentence-guided grid tagging scheme and its decoding method, which can obtain great performance in labeling explicit and implicit opinion quadruple. Experiments demonstrate that our SGTS-AQSE model outperforms the state-of-the-art baselines for the ASQE task.

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Author Contributions Xiangjie Kong and Yinwei Bao wrote the main manuscript text. Xiangjie Kong contributed to the overall design of the study and some experimental designs. Yinwei Bao designed the model and analysed the data. Minhao Xu prepared figures 1-4, and Yinwei Bao prepared figures 5. Yinwei Bao, Minhao Xu, and Zhechao Zhu did the experiments. Zhechao Zhu prepared table 1-5. All authors reviewed the manuscript.

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Data Availability Two datasets used in this work are publicly available, and can be downloaded at https://github.com/NUSTM/ACOS/tree/main/data.

Declarations

Competing interests The authors declare that they have no competing interests.

Ethical Approval Not applicable.

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